Cognitive Systems

# Generic framework for simulation of cognitive systems: a case study of color category boundaries

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# Research question

The generic model of an cognitive system is presented here, where a symbol couples dynamic behavior of two cognitive systems, therefore functionally constraining its function. In most agent-based models of communication, symbols are treated in the traditional manner – as entities that can be mapped to external objects. These models assume that semantics can be unequivocally ascribed to a symbol.

# Earlier work

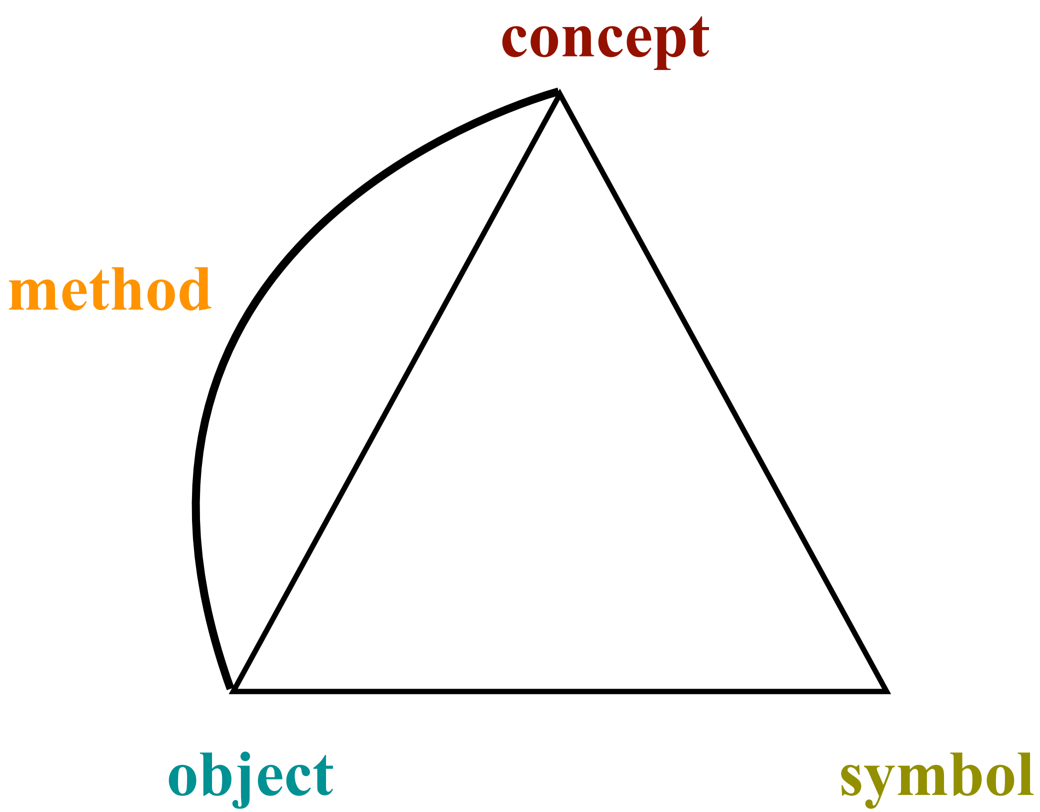
The work is founded of earlier works by Steels and Belpaeme (2005), who analyzed the cultural emergence of colour categories using their original modeling framework. Agent-based model of cultural emergence of colour categories shows that boundaries might be seen as a product of agent's communication in a given environment.

# Cultural and ecological context

We propose the generic agent-based modeling framework of cultural emergence of colour categories shows that boundaries might be seen as a product of agent's communication in a given environment. We therefore underscore external constraints on cognition: the structure of the environment, in which a system evolves and learns and the learning capacities of individual agents.

# Cognitive systems: definitions

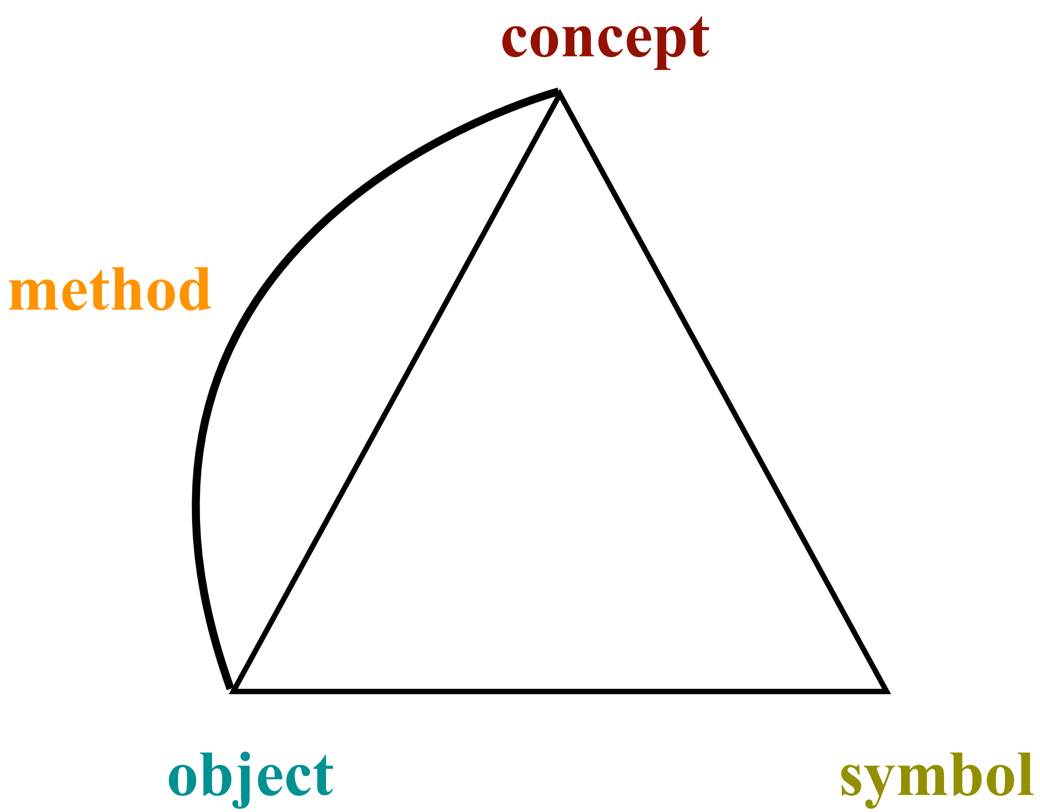
# Semiotic Triad




**Semiotic Triad** relates a symbol, an object, and a concept applicable to the object. The method is a procedure to decide whether the concept applies or not.

Pierce

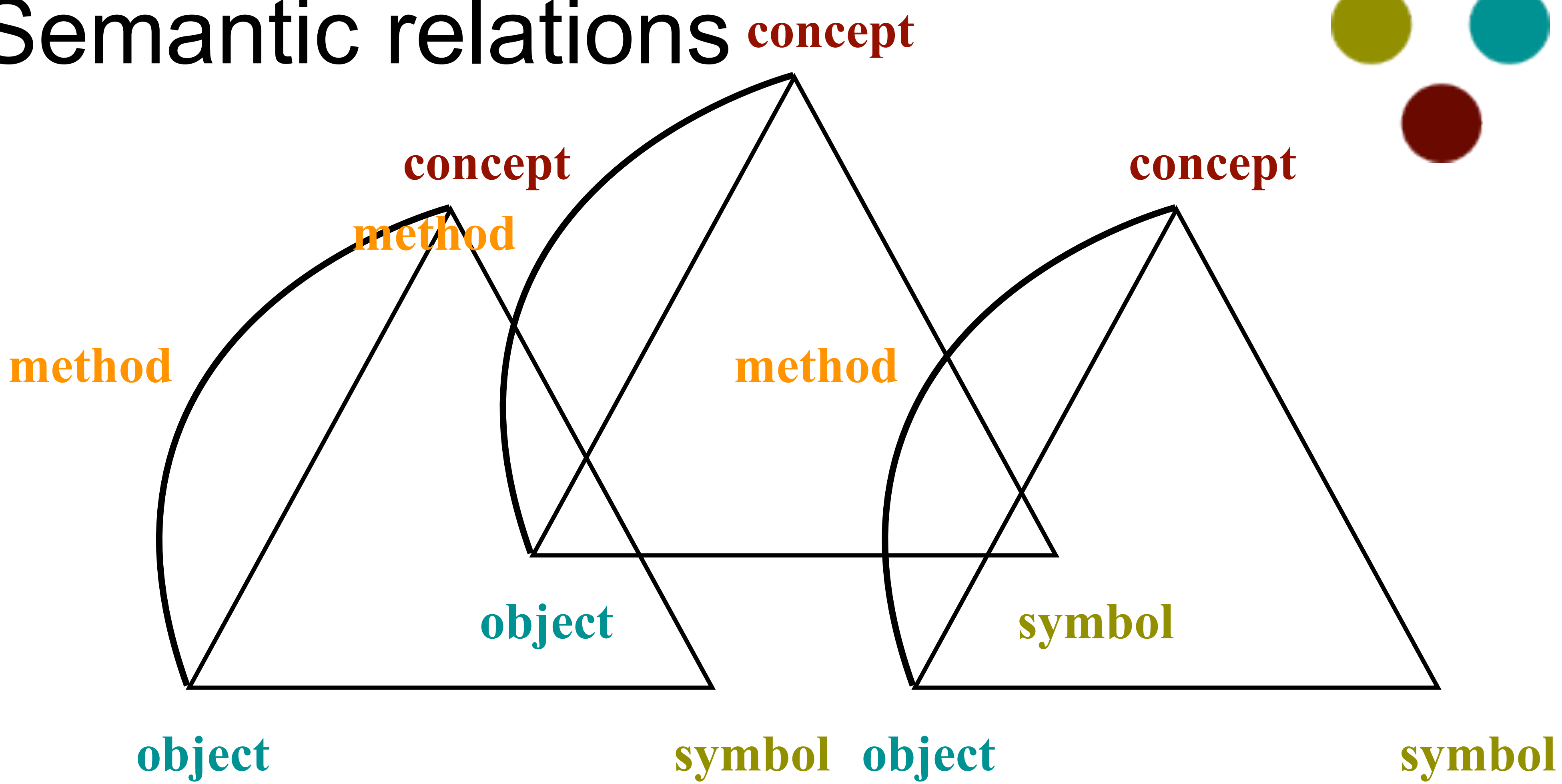
# Semiotic Triad




**Method** constrains the use of symbol for the objects with which it is associated: a classifier, a perceptual/pattern recognition process that operates over the sensori-motor data to decide whether the object "fits" with the concept.
If such an effective method is available, then the symbol is **grounded** through perceptual process.

L. Steels

# Semantic relations

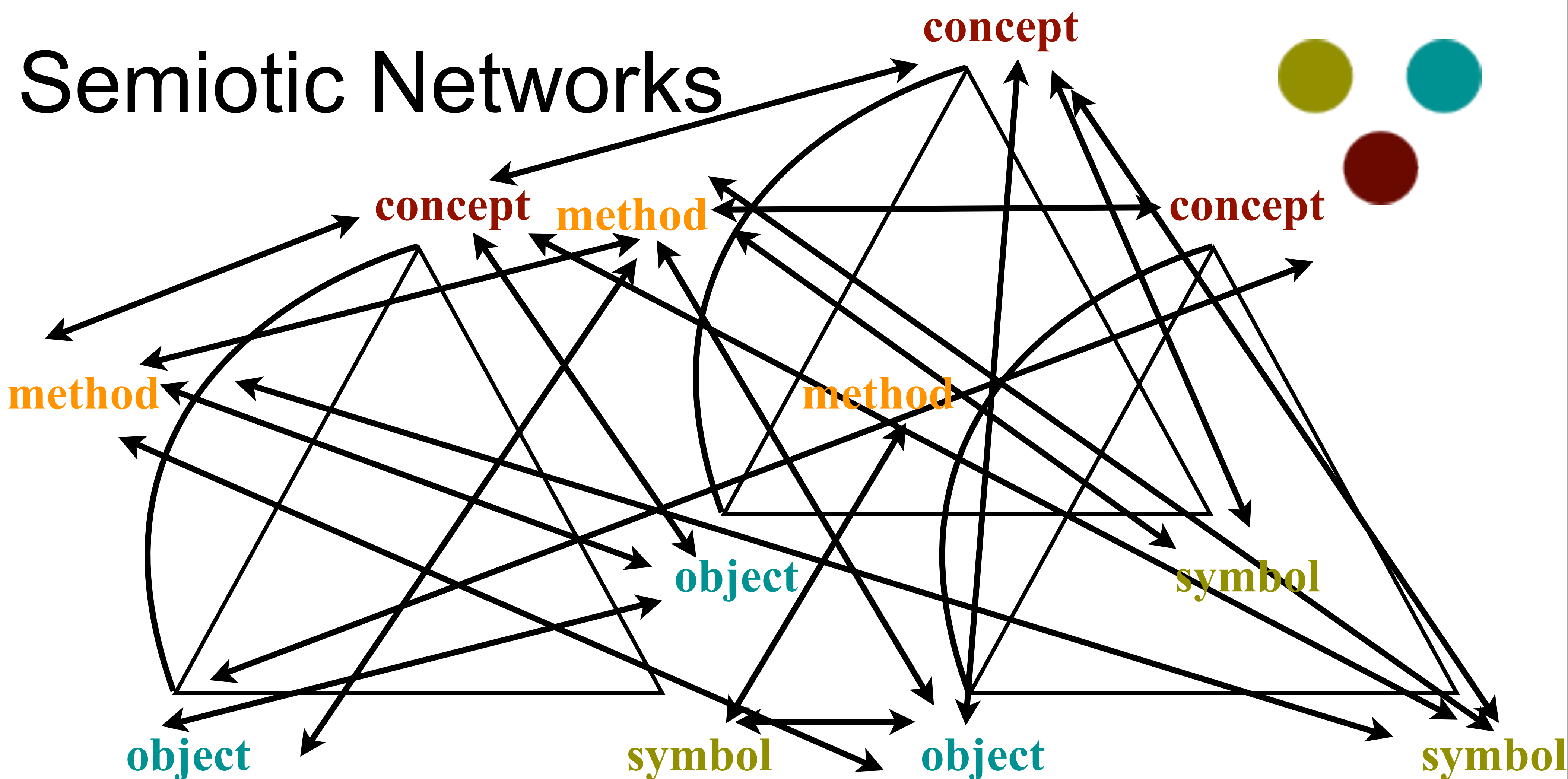



**Semantic relations** provide pathways for navigations between concepts, objects, and symbols:

- objects occur in a context (spatial and temporal relations)
- symbols co-occur with other symbols
- contepts may have semantic relations among each other
- methods can be also related

L. Steels

# Semiotic Networks




**Semiotic network** is a set of links between objects, symbols, concepts and their methods.
Every individual maintains such network, and it is dynamically modified/expanded/reshuffled every time we experience, think, interact with world or with others.

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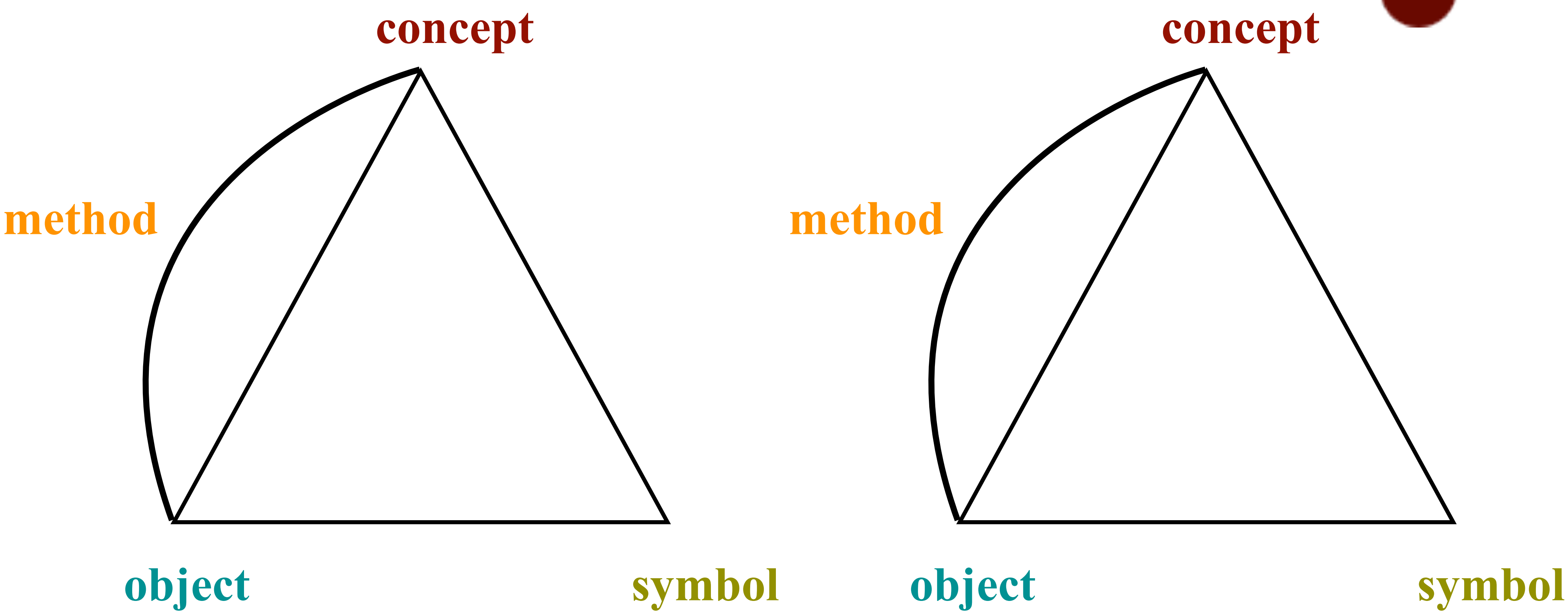
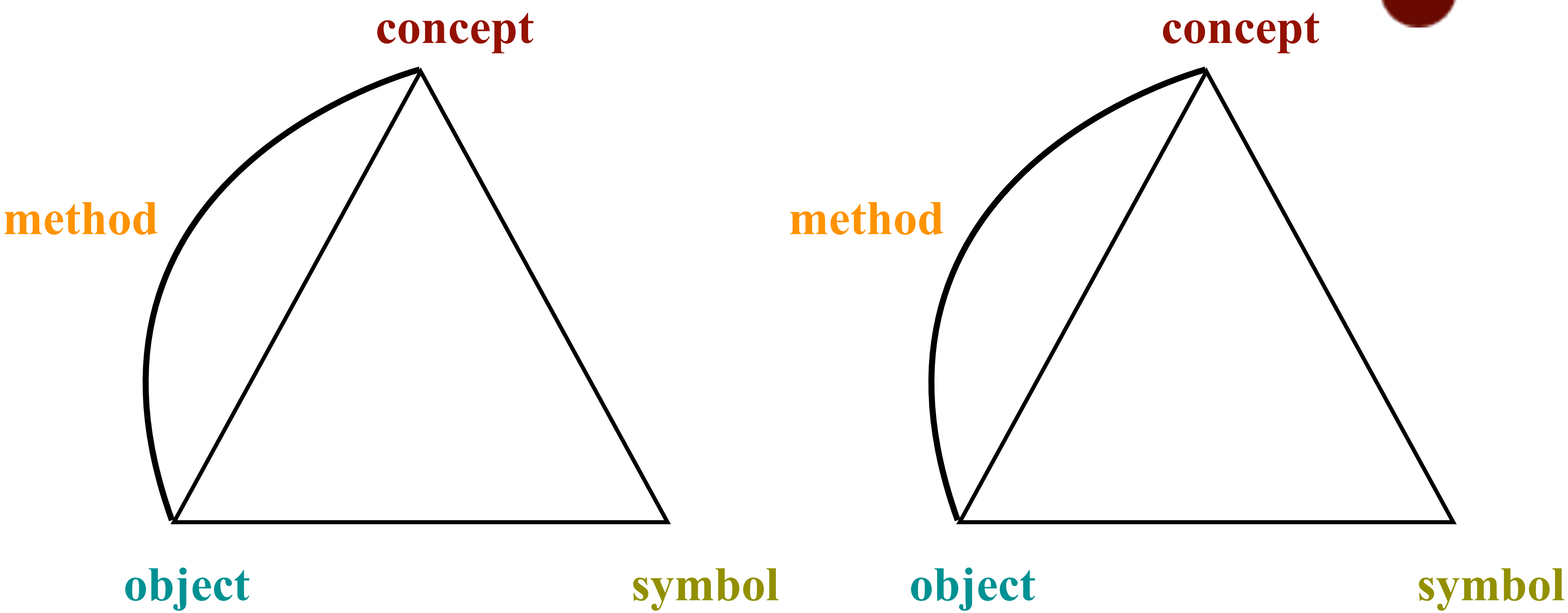
# Communication




Individuals navigate through the semiotic network for purposes of communication.

*"When a speaker wants to draw the attention of an addressee to an object, he can use a concept whose method applies to the object, then choose the symbol associated with this concept and render it in speech or some other medium. The listener gets the symbol, uses his own vocabulary to retrieve the concept and hence the method, and applies the method to decide which object might be intended."* L. Steels

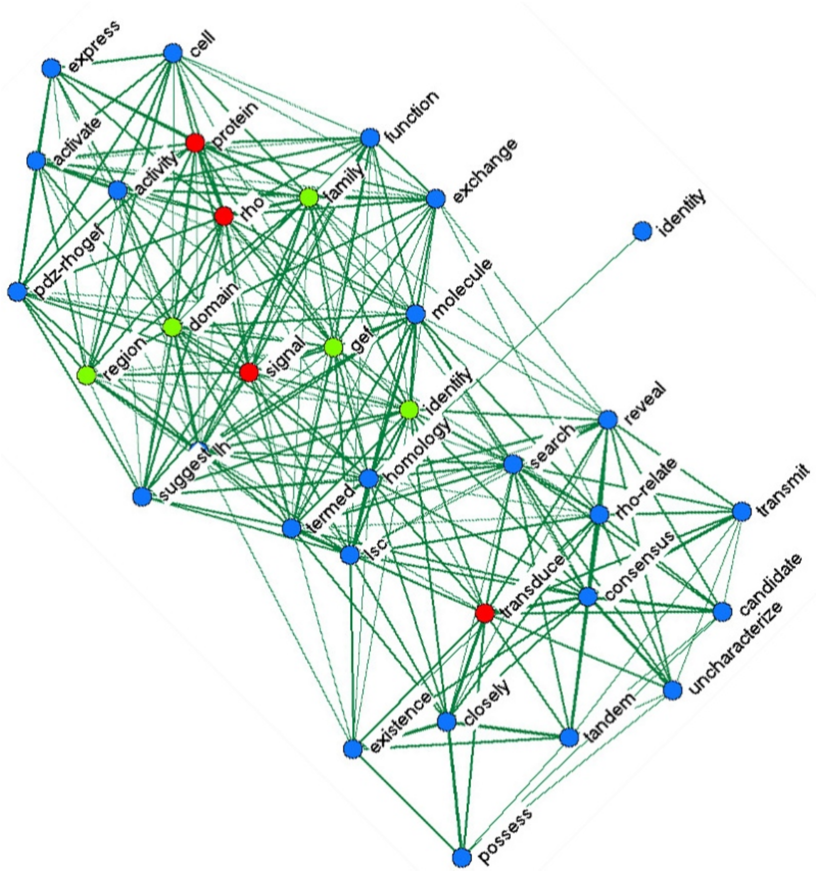
# Communication

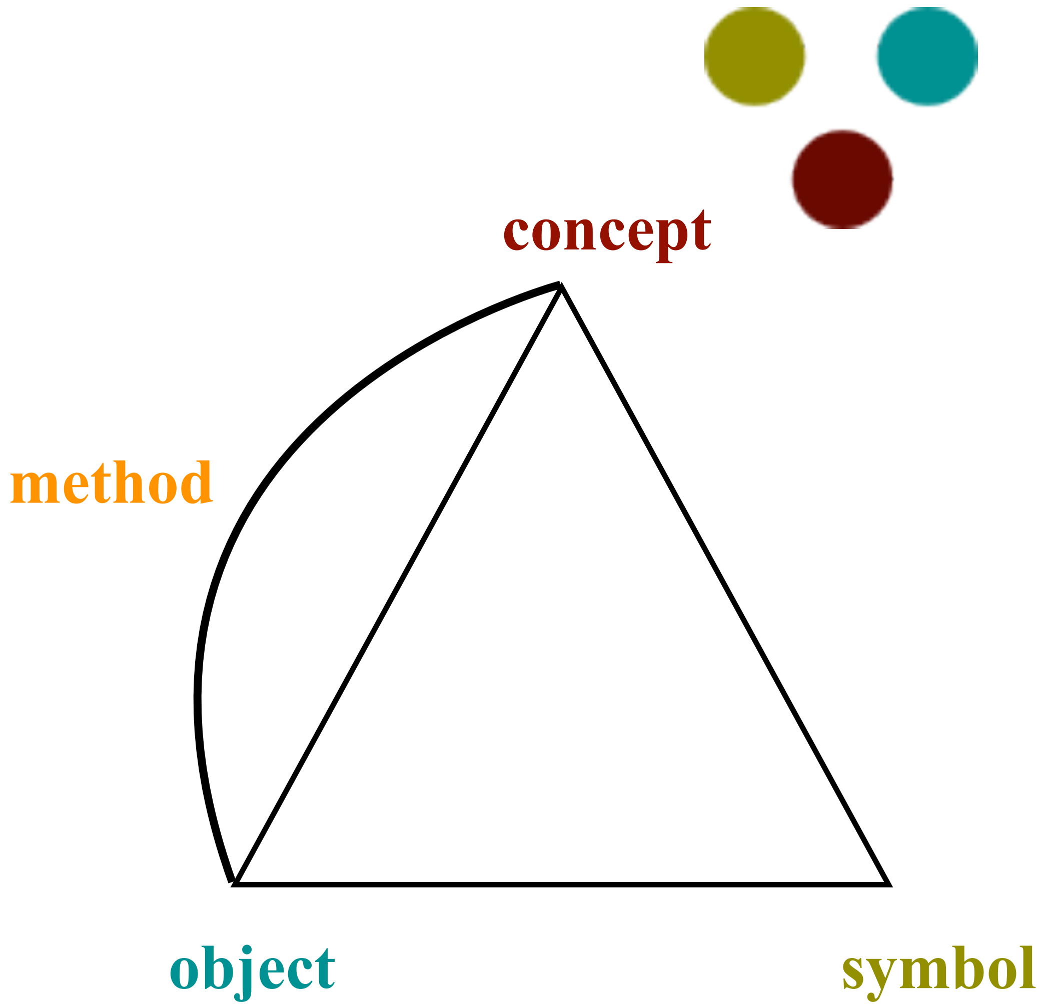



Speakers and hearers adopt and align their communication systems at all levels within the course of a single communication.

Their sound systems and gestures become similar, they adopt and negotiate new word meanings, they settle on certain grammatical constructions, they align their conceptualizations of the world.

# Adaptation

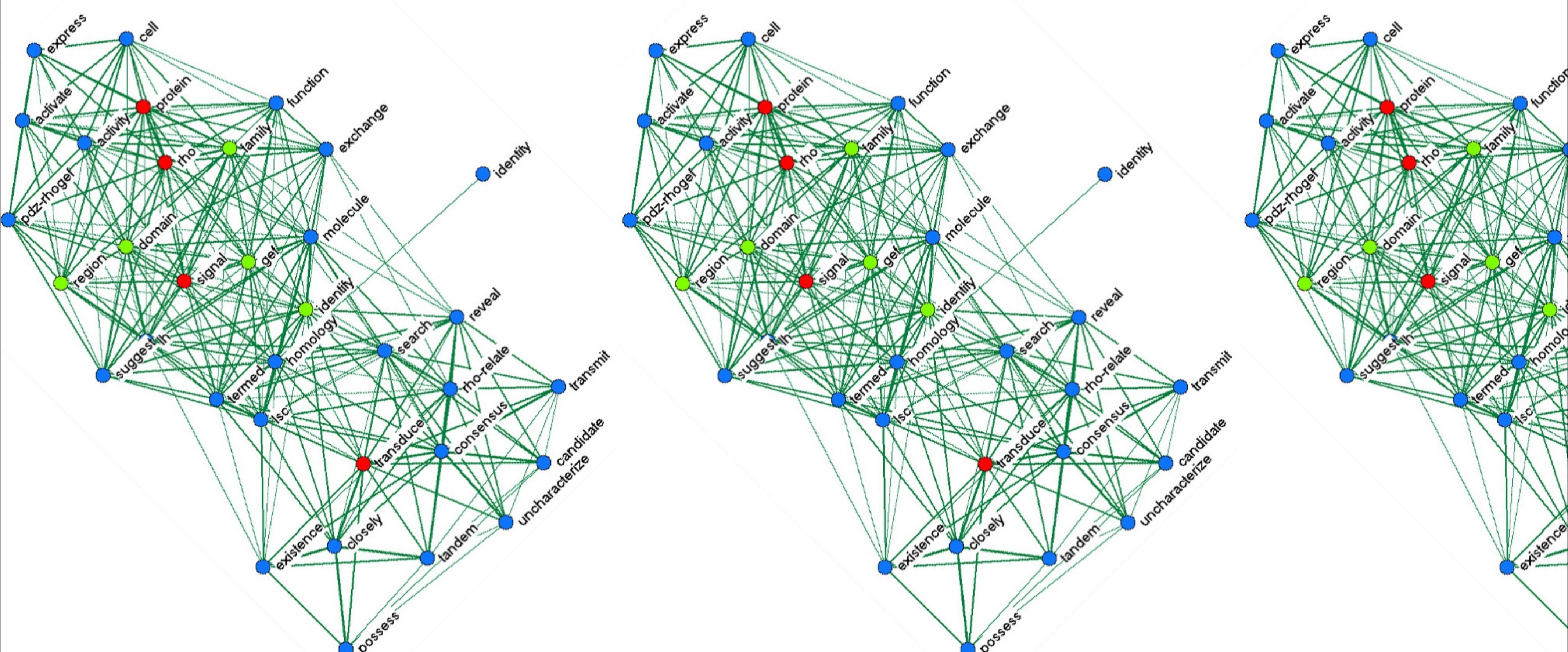



Progressive and continuous adaptation of semiotic networks

In communication partners get feedback on how their own semiotic networks are similar or divergent from those of others -> therefore they are coupled via binary interactions and get progressively coordinated in a group.

# Semiotic landscape

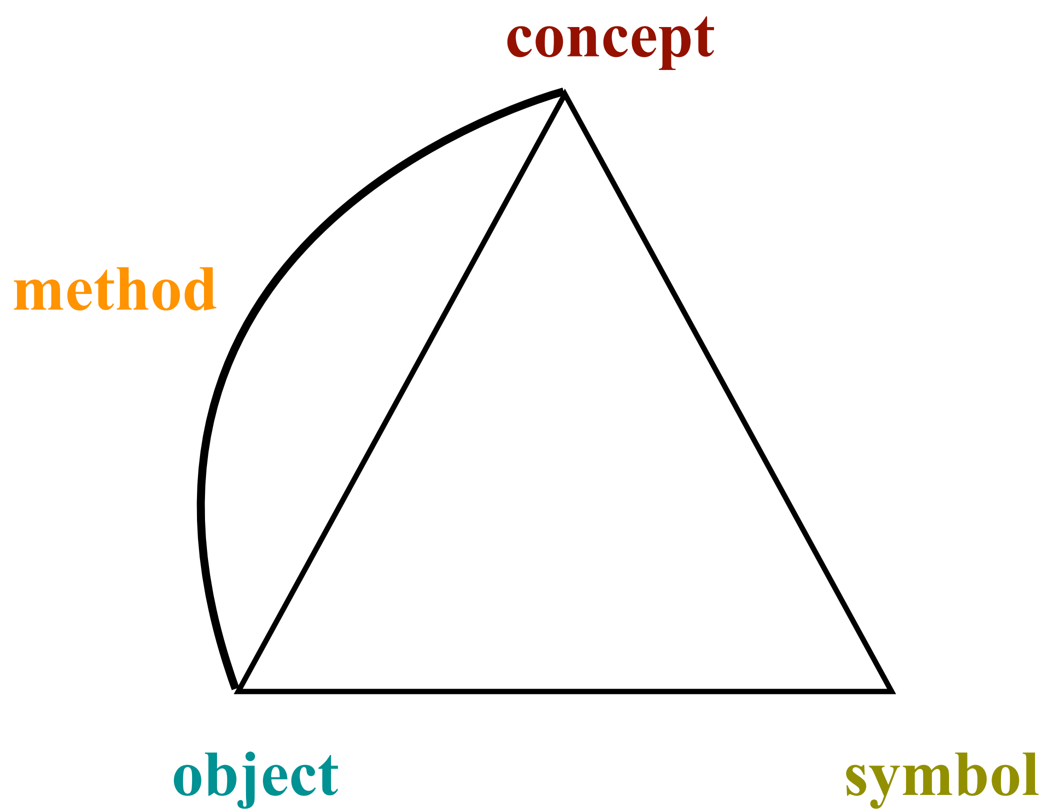



The set of all semiotic networks of a population of interacting individuals.

It is undergoing continuous change as every interaction may introduce, expand, or enforce certain relationships in the networks of individuals.
Even though there are strong tendencies towards convergence, yet individual semiotic networks will never be exactly the same.

L. Steels

# Symbol Grounding




Searle (1980): can a robot deal with grounded symbols?

Is it possible to build an artificial system that has a body, sensors and actuators, signal and image processing and pattern recognition process, and information structures to store and use semiotic networks, and uses all that for communicating about the world or representing information about the world?

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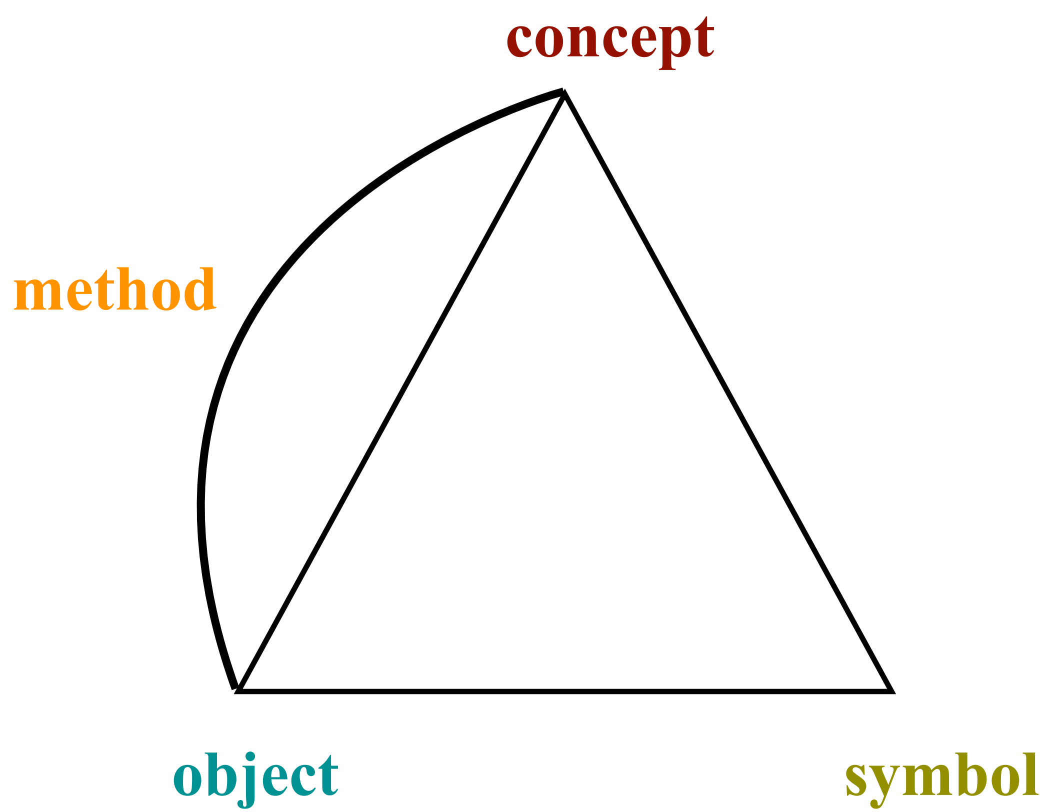
# Semantic came from us, humans




Computational systems cannot generate their own semantics, whereas natural systems (human brains) can.

Brain is capable to develop autonomously a repertoire of concepts to deal with environment and to associate them with symbols which are invented, adopted, and negotiated with others.

L. Steels

# Artificial cognitive systems

System that autonomously establishes the semiotic network that it is going to be used to relate symbols with the world.

Deb Roy (2007) Artificial Learning System: example sentences and example situations to a vision-based robotic system and the robot acquire progressively effective methods to use these symbols in subsequent real world interaction.

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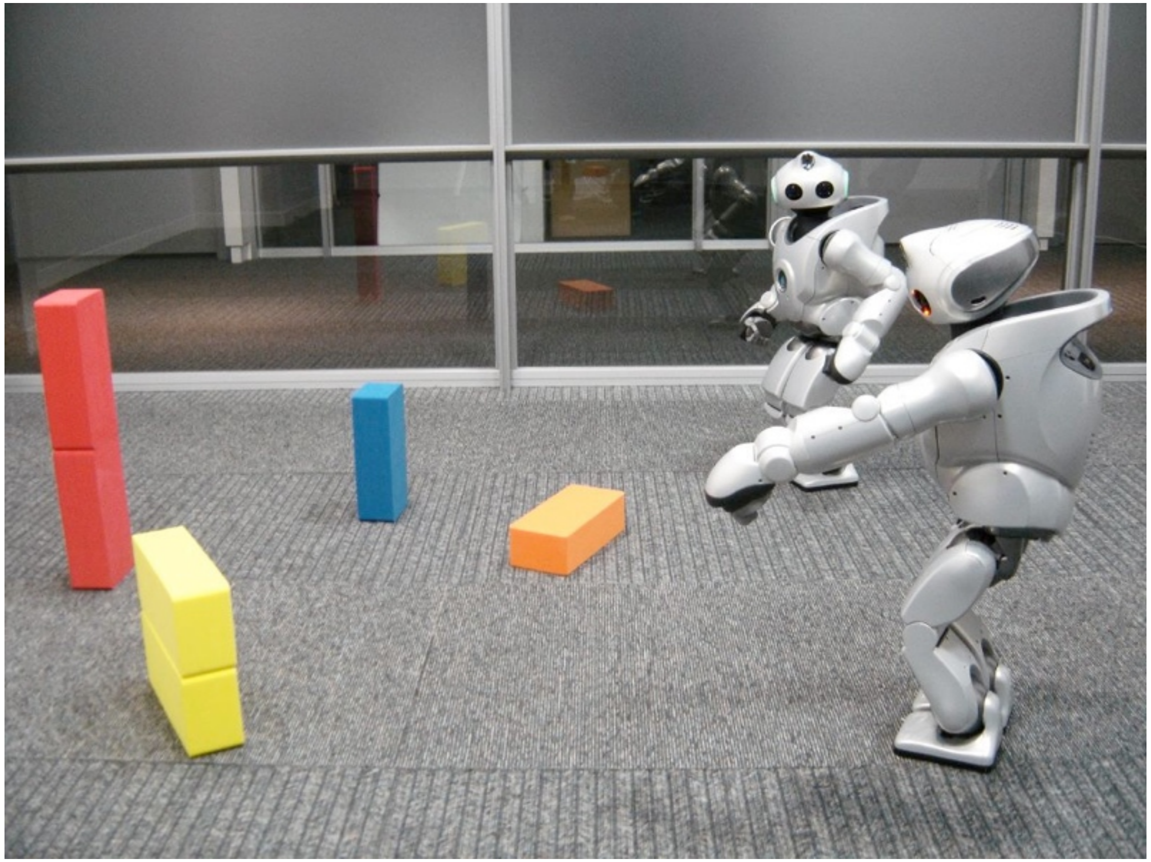
# Sources of Meanings



A mechanism by which an agent can autonomously generate its own meanings.

There must be distinctions that are relevant to the agent in his agent-environment interactions, a way to introduce new distinctions, and a task setting. For example language games (routinized situated interaction between two embodied agents who have a cooperative goal).

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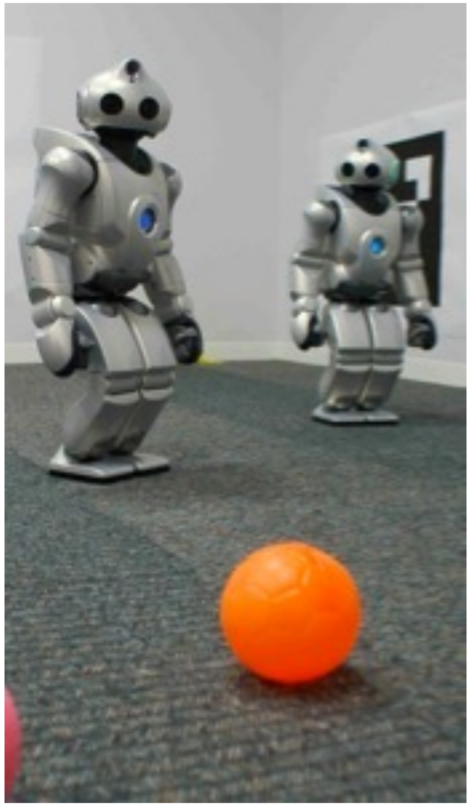
# Grounding of Categories



A mechanism by which an agent can internally represent and ground their relevant meanings.

No prior inventory of categories and no inventory of methods (classifiers) that apply categories to the features (sensory experience) they extracted from the visual sensation they received through their cameras. In Steels work a category is distinctive for a chosen topic if the color of the topic falls within the region around particular prototype and all other samples fall outside of it.

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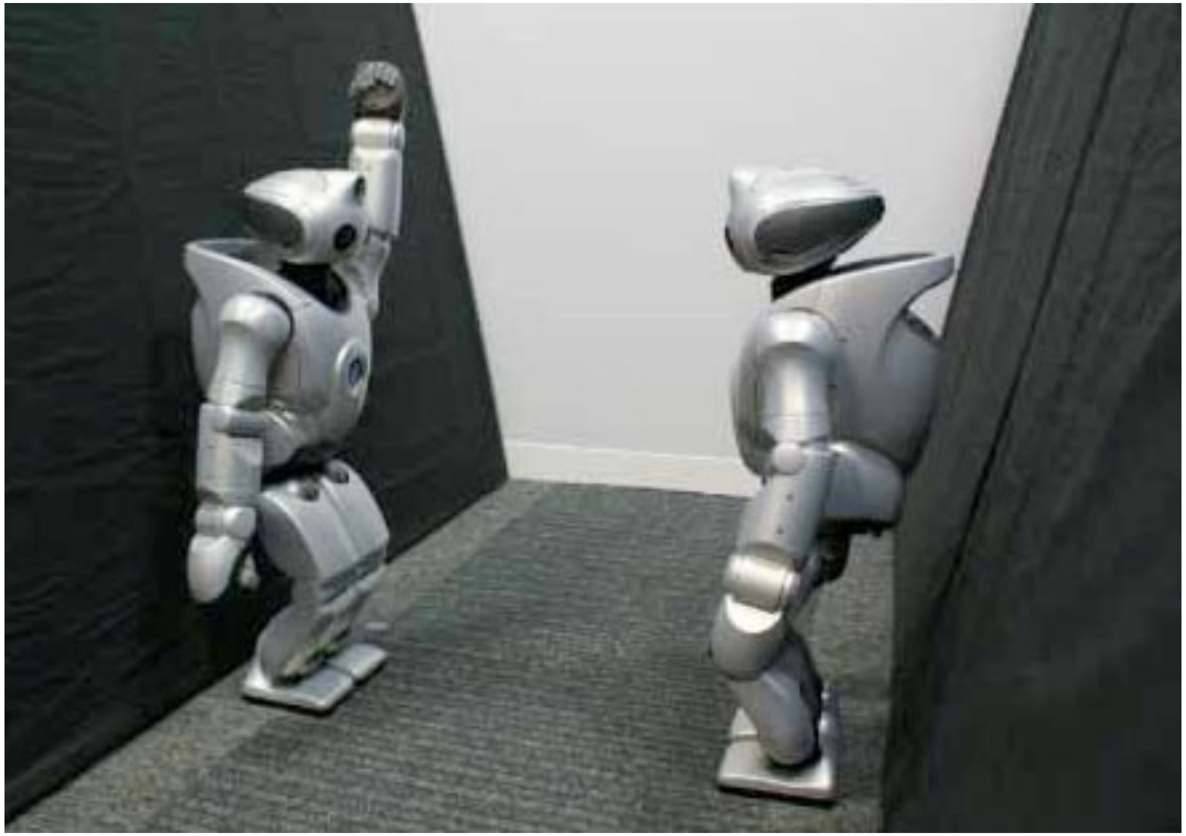
# Self-organization of symbols



Agents autonomously can establish and negotiate symbols to express the meaning that they need to express.

New symbols are generated by combining randomly a number of syllables into a word. The meaning of a word is a perceptually grounded category. No prior lexicon is given to the agents, nor is there any central control that determine by remote control how each agent has to use a word.

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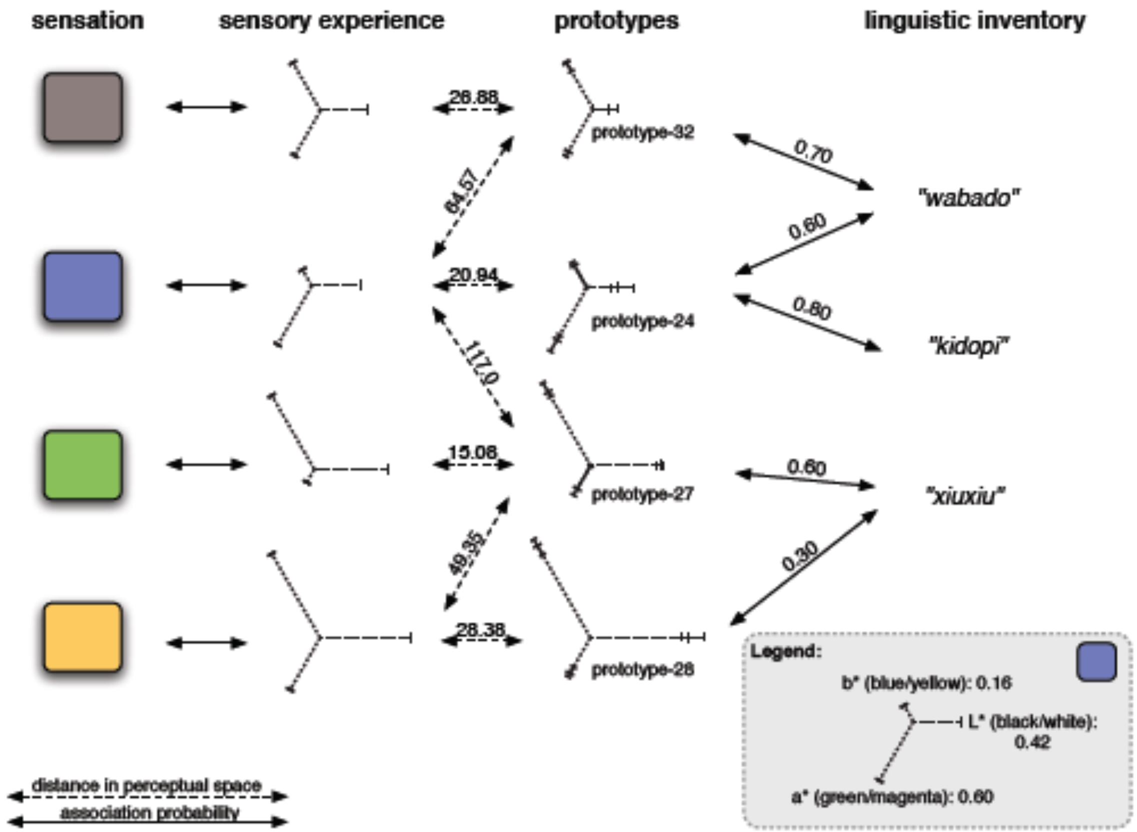
# Self-organization of symbols




Semiotic network for a single agent, linking sensations to sensory experiences, prototypes, and symbols.

A speaker invents a new word when he does not have a word yet to name a particular category and a hearer will try to guess the meaning of the unknown word based on feedback after a failed game and thus new words enter into the lexicons of the agents and propagate through the group.

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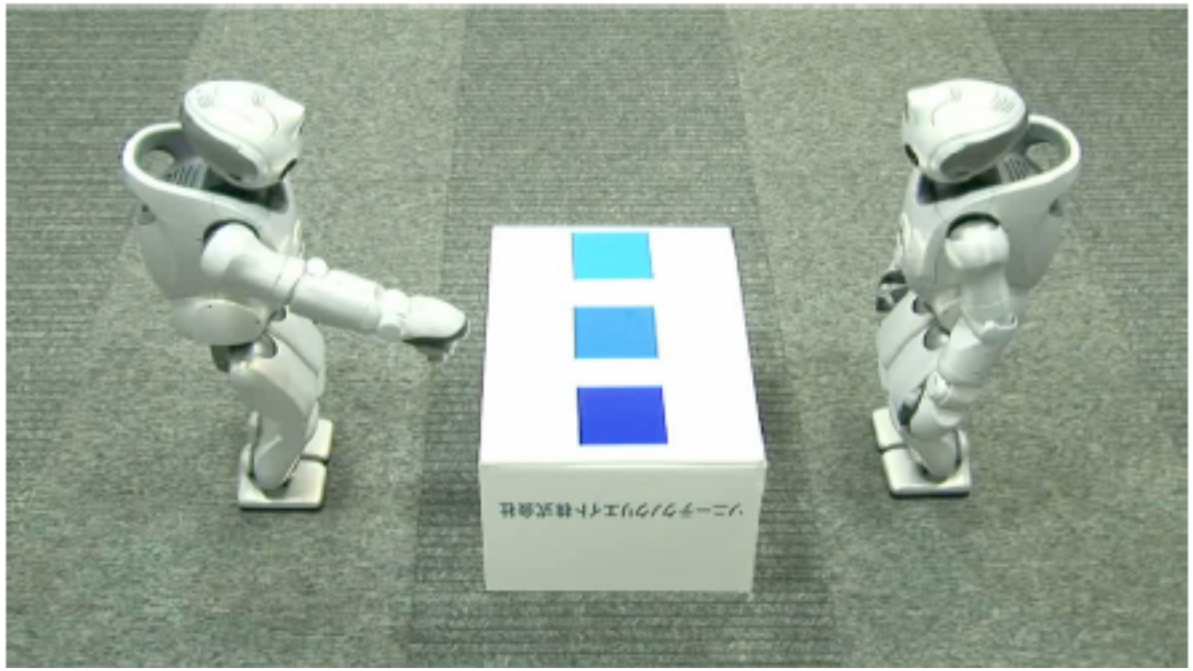
# Coordination process



Coordination creates the semiotic dynamics so that the semiotic networks of the individual agents become sufficiently coordinated to form a relatively organized semiotic landscape.

Speakers and hearers continue to adjust the score of form-meaning associations in their lexicon based on the outcome of a game, so that the population settles on a shared lexicon.

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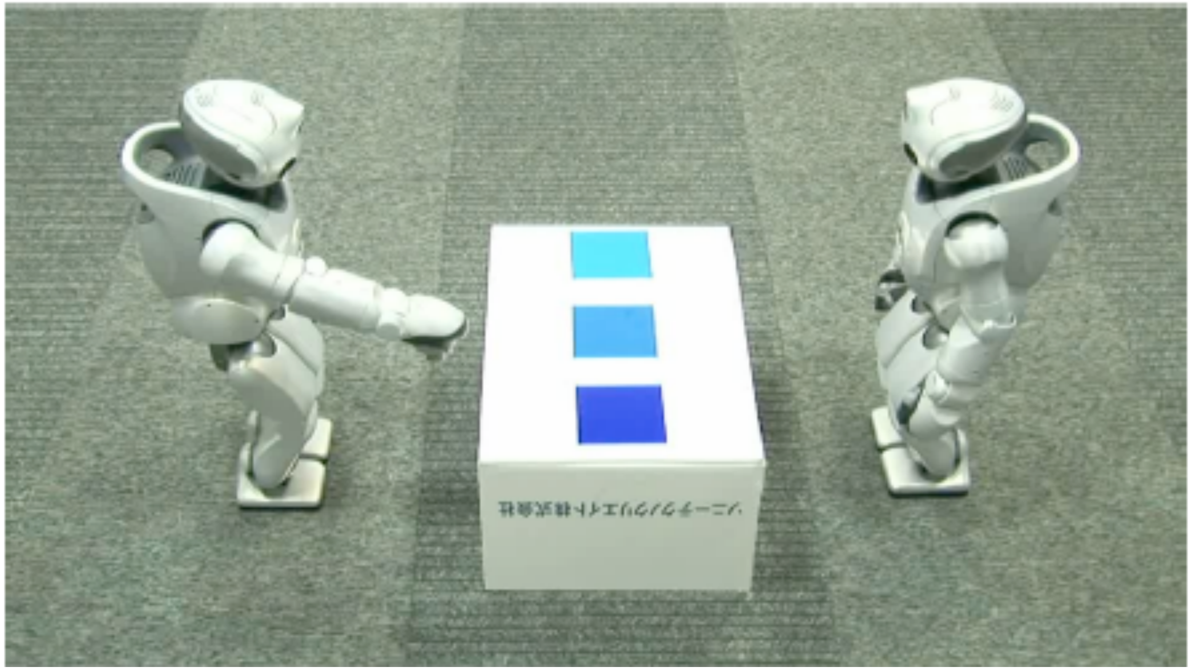
# Coordination process



Coordination creates the semiotic dynamics so that the semiotic networks of the individual agents become sufficiently coordinated to form a relatively organized semiotic landscape.

Speakers and hearers also maintain scores about the success of perceptually grounded categories in the game, and they adjust these scores based on the outcome, so that the perceptually grounded categories get also coordinated.

L. Steels

# Cognitive Systems Simulations: *a generic framework*

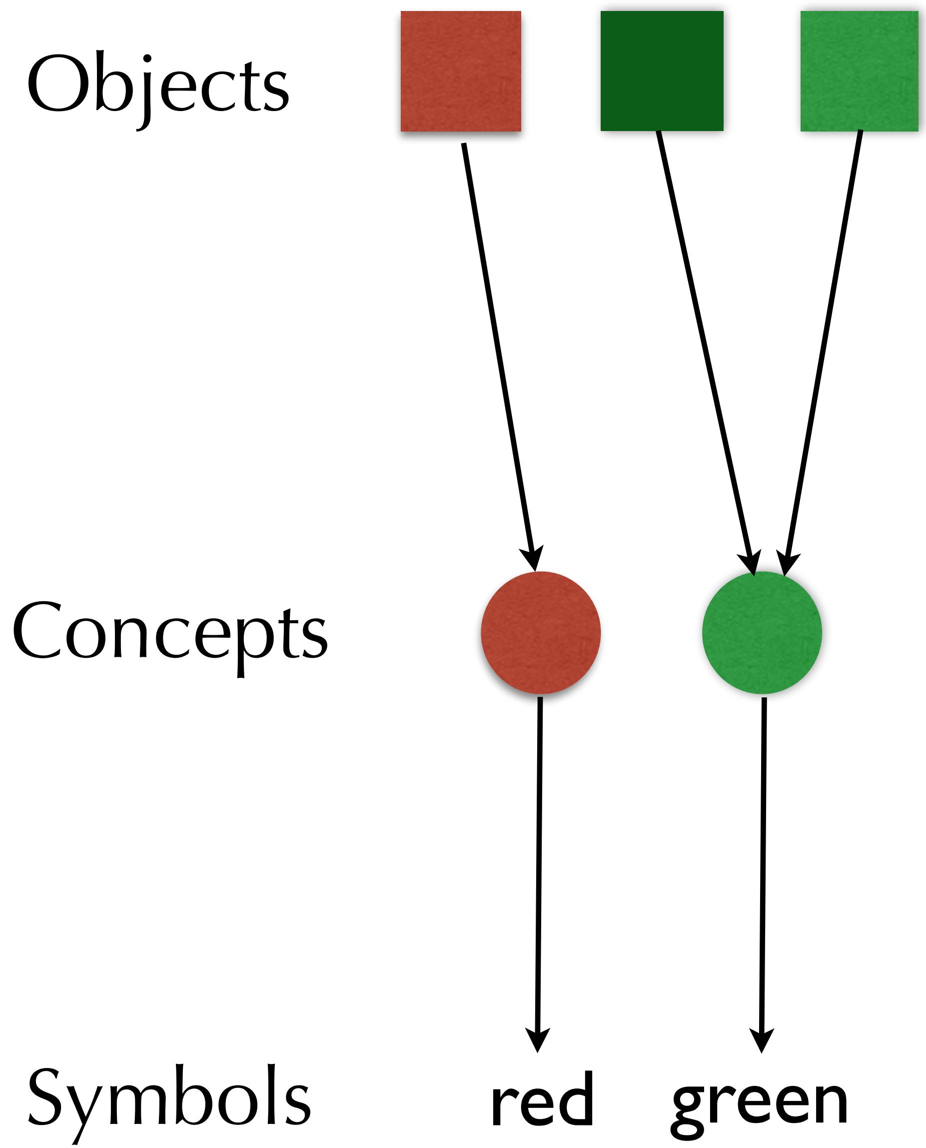
# Agent based modeling

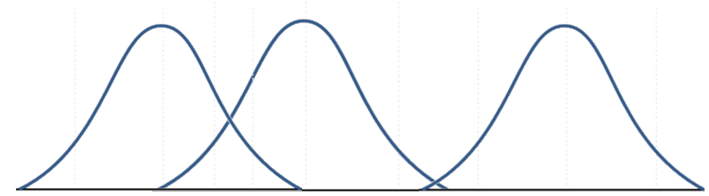
**N agents**
Each agent gets a stimuli with an context.
Stimuli is a color from Munsell pallette (330 or 1269 colors).


**Each of agents:**

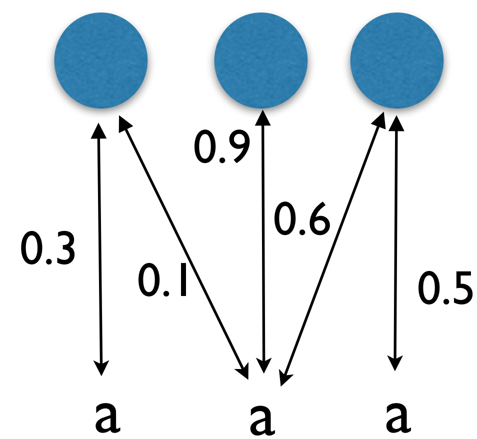
- has its own categorization system (discriminative task)
- has its lexicon shared among population (linguistic categorization)

# Agent architecture

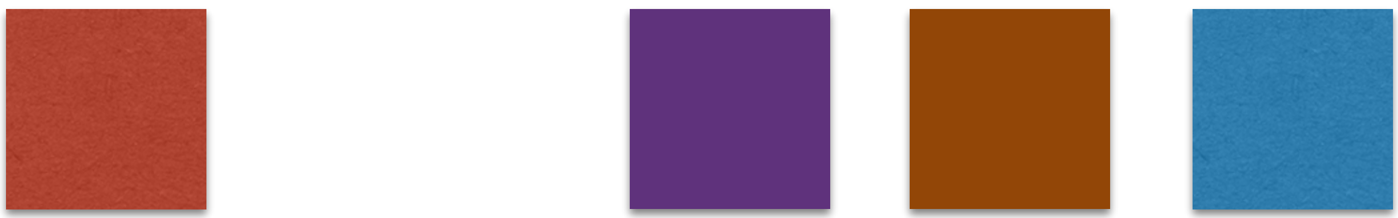


$$z_j(\mathbf{x}) = e^{-\frac{1}{2}\sum_{i=1}^{N}\left(\frac{x_i - \mathbf{m}_{ji}}{\sigma}\right)^2} \qquad y_k(\mathbf{x}) = \Sigma w_j z_j(\mathbf{x})$$



# Discrimination game

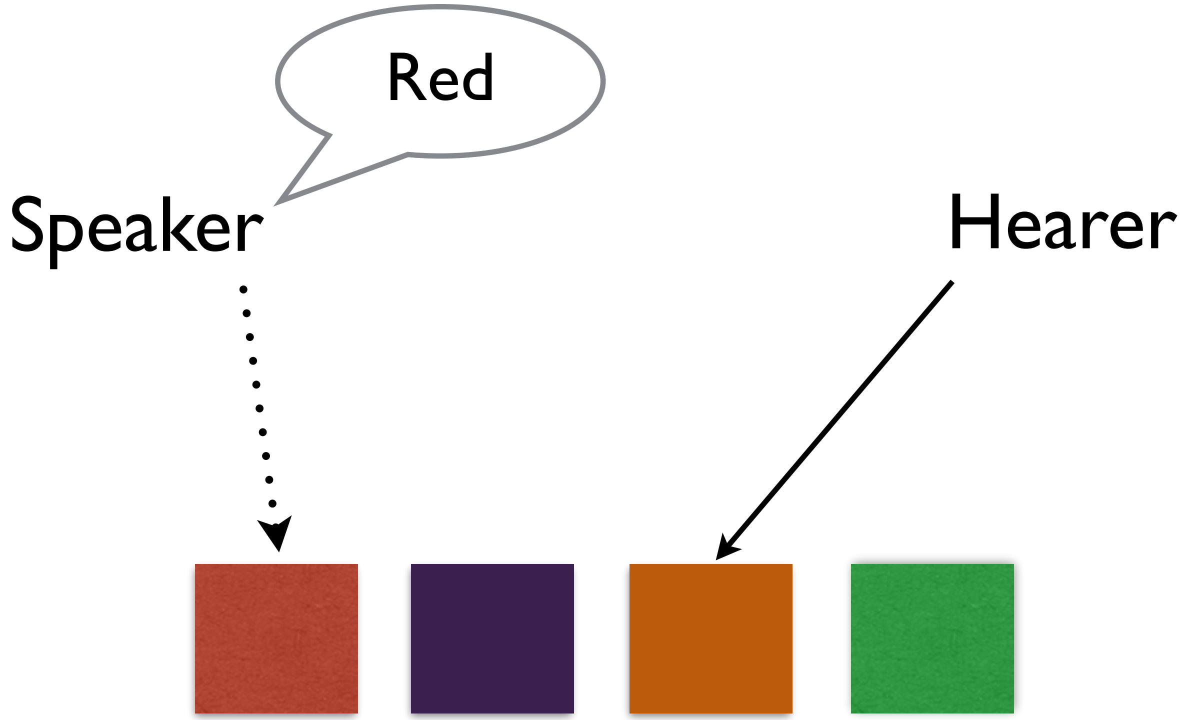


Topic Context

**Discrimination game (classification)**
- cognitive process, which process stimuli from an environment and learns to distinguish them.

Discriminative categories are implemented by linear combination of  centroids.

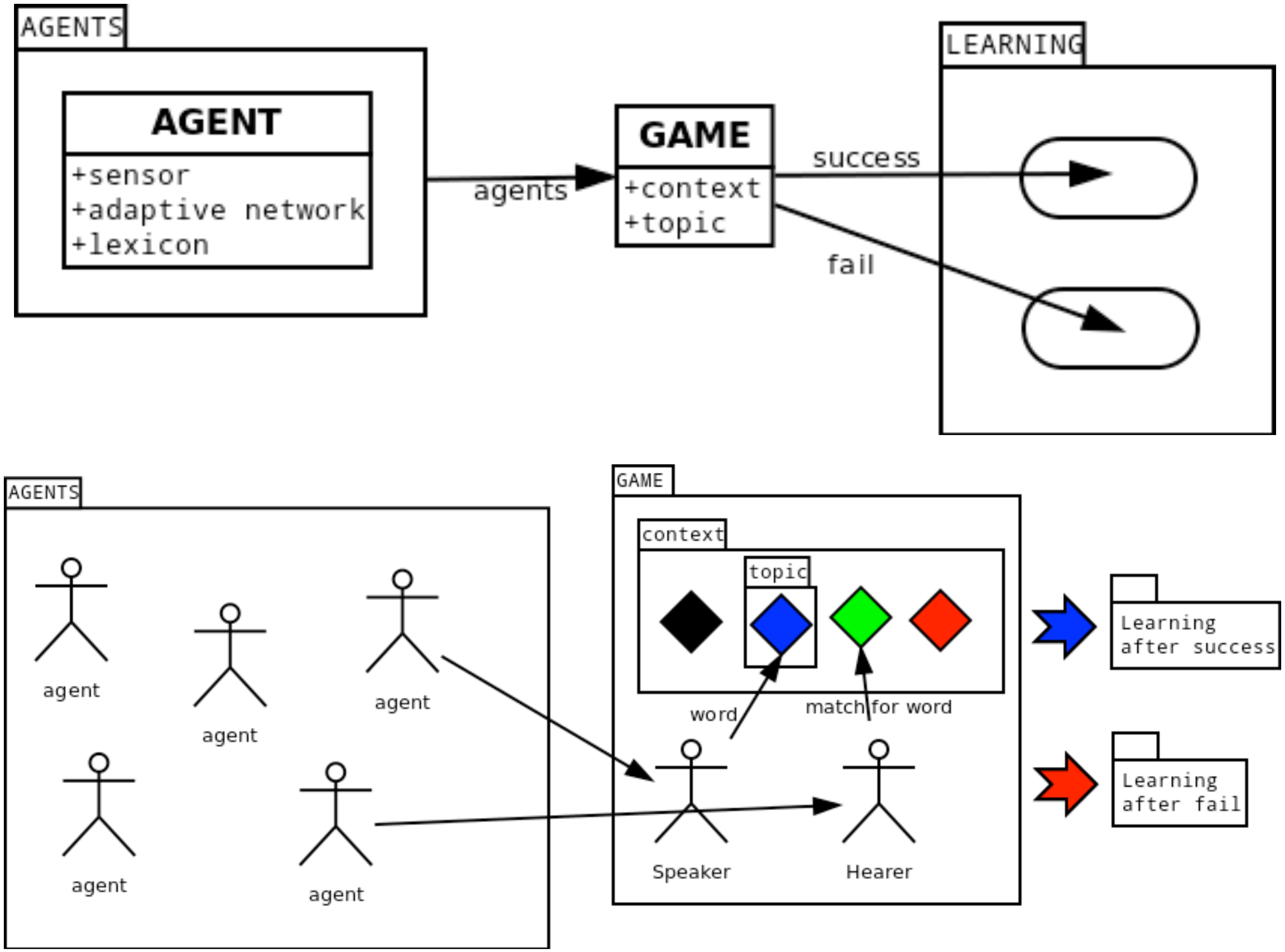
# Guessing game



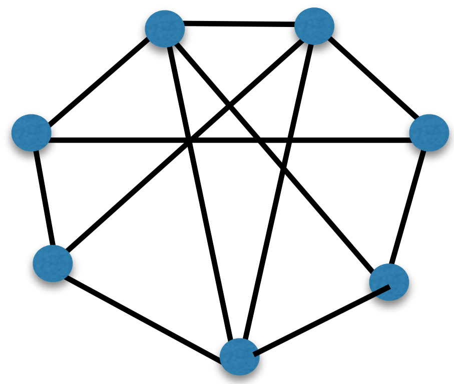

**Guessing game (naming)**
- the process of naming sharing among population of agents. Speaker and hearer are participating.

The outcome of this game are **linguistic categories** grounded with selected stimuli.

# Simulation framework



# Simulation framework



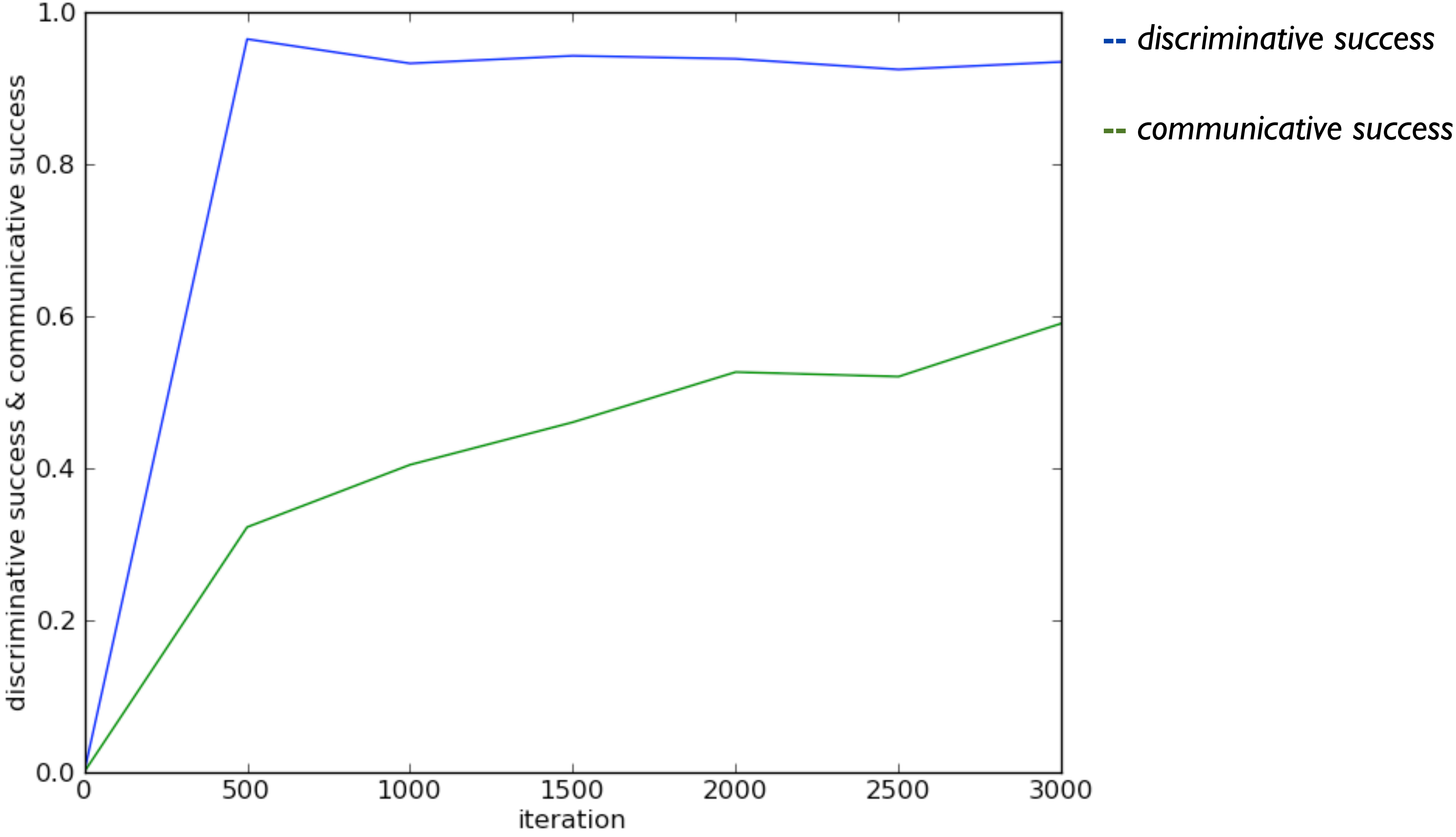
In each iteration interaction between one randomly selected pair of agents occur.

Fully connected interaction graph

We can measure:

- fraction of successfull discrimination games over certain period,
- fraction of successfull guessing games over certain period,
- variance of categories between agents.

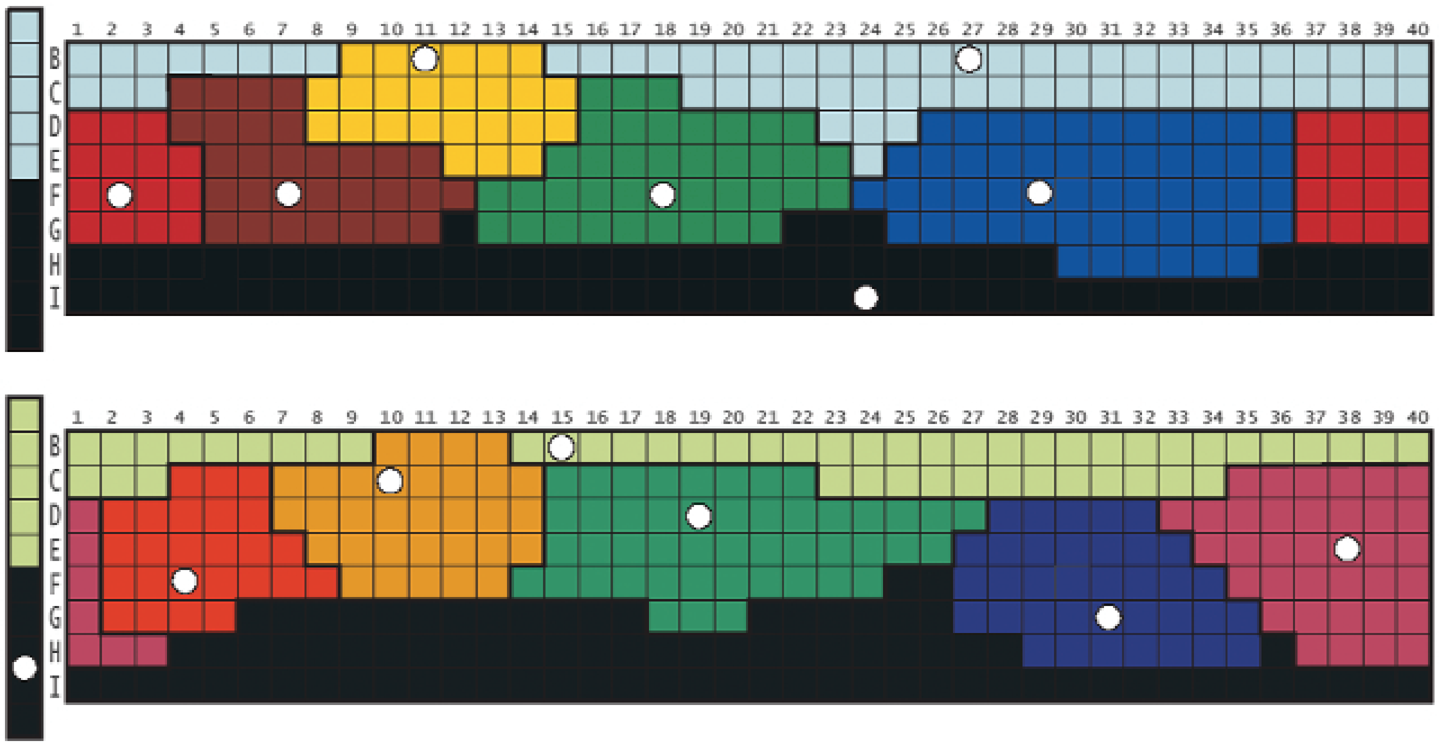
# Examples



1.0
0.8
0.6
0.4
0.2
0.0
0
500
1000
1500
2000
2500
3000
iteration
discriminative success & communicative success
-- discriminative success
-- communicative success

# Examples

Categorization of colors for two agents



# Lexicon acquisition

Speaker and hearer after interaction:

- if the guessing game was successful, increase weights of the used category,
- if the guessing game was not successful, decrease weights of the used category.

If speaker lacks proper word, he invents it. If hearer does not know the word, he asks the speaker to point correct object and remembers the new word with discriminative category.

# How the categories are learned?

1. Nativism - we are born with the same set of categories, only words are learned.
2. Empiricism - we share the same inductive learning mechanisms, so given the same set of stimuli we produce the same set of categories.
3. Culturalism - language coordination is needed to further refine categories (i.e. language provides mechanisms to optimise itself).

# How the categories are learned?

Nativism:

Genetic algorithm is used to optimize categories. Discriminative game success is used as fitness. In each generation 50% of the fittest agents survive and produce mutated offspring. There are four possible mutations:

1. New category with one random reactive unit.
2. Existing category expanded with an additional unit.
3. Unit removed from existing category.
4. Category removed.

# How the categories are learned?

Empiricism:

Learning after discriminative game.

When successful: increase weights of units in network connected with winning category.

When not successful: if no categories or DGS < 95%, create a new category. Otherwise, adapt existing category.

# How the categories are learned?

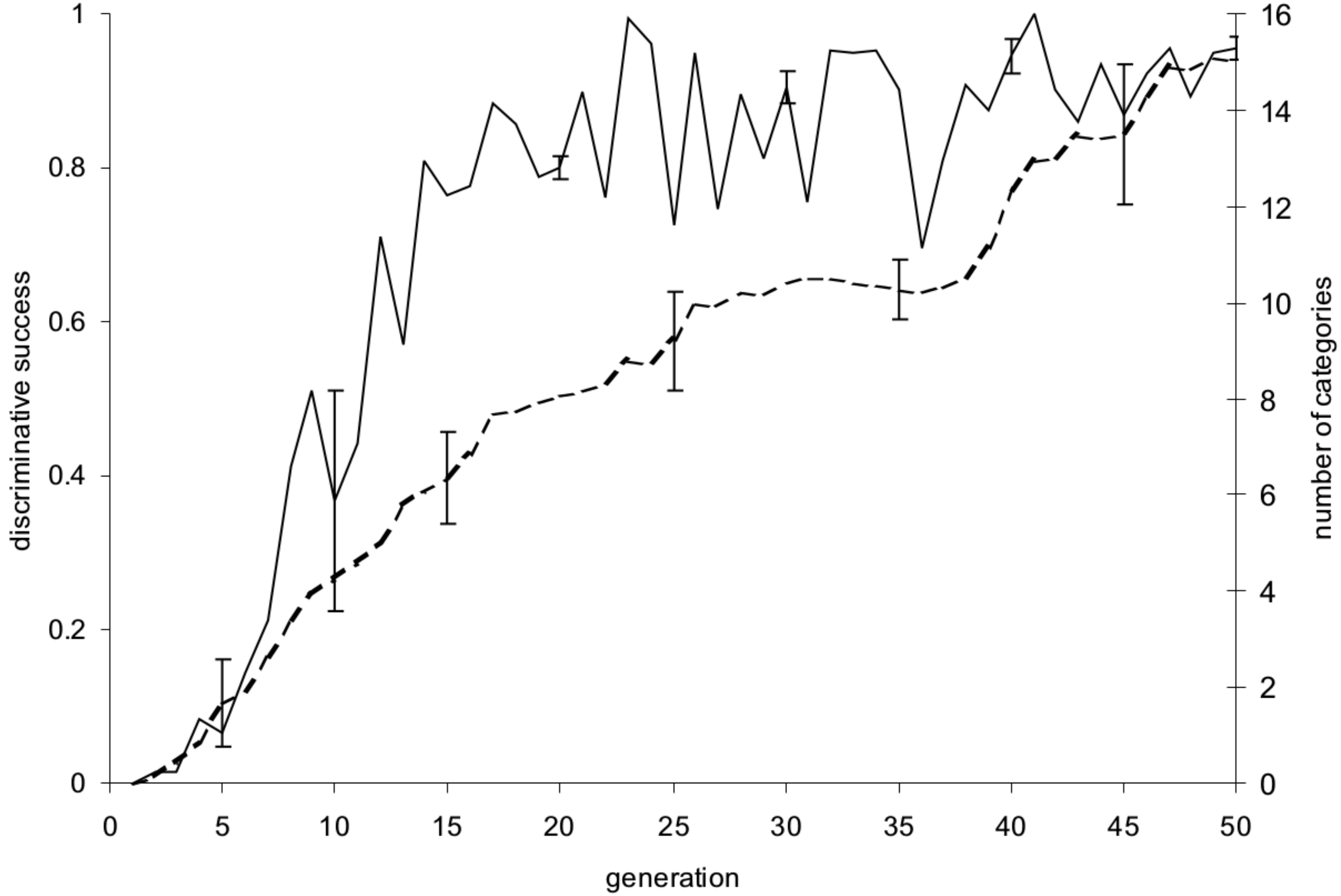
Culturalism:

Learning after discriminative game and guessing game.

When successful (GG): increase weights of units in network connected with winning category.

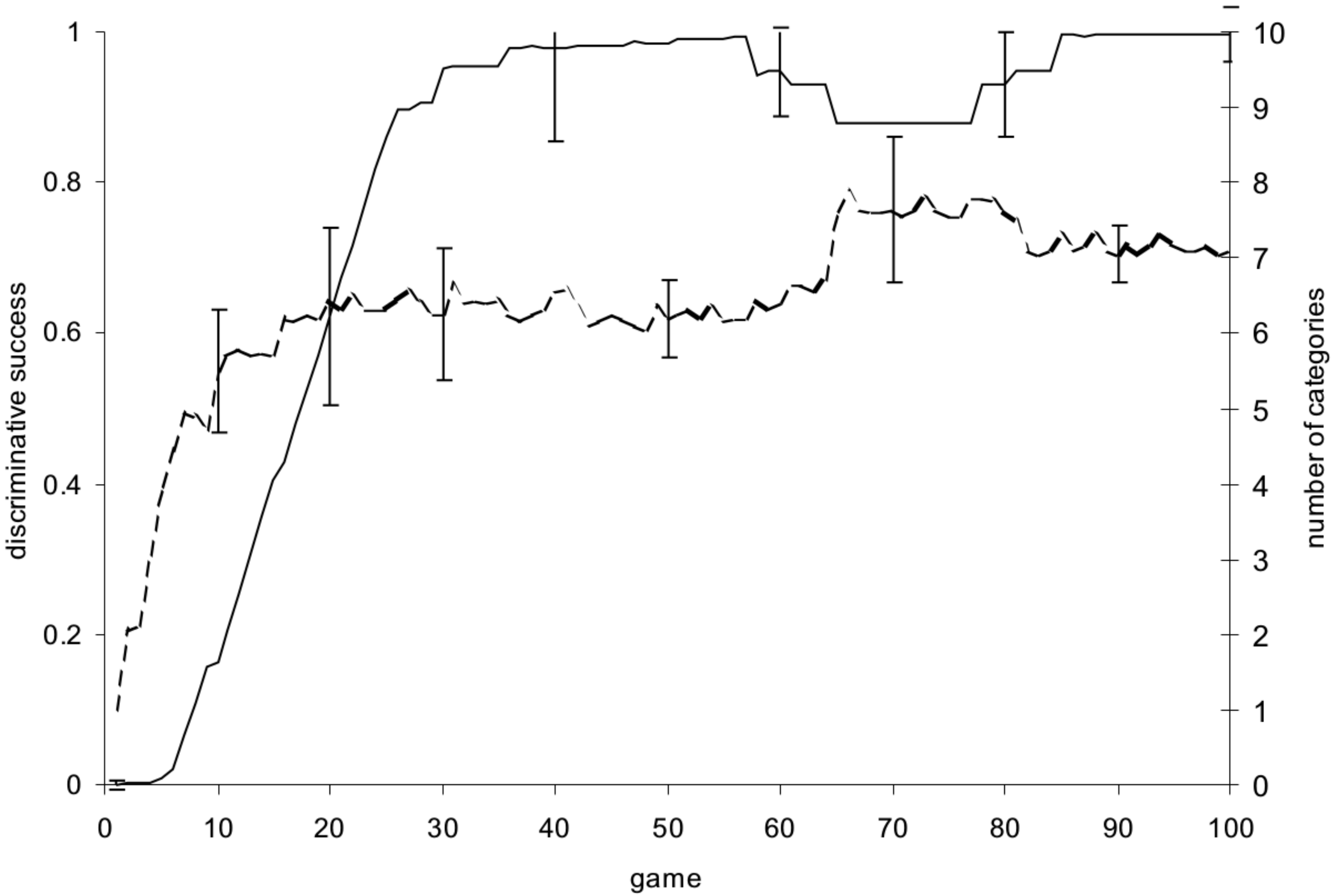
# Effectiveness of learning

Discriminative success: nativism



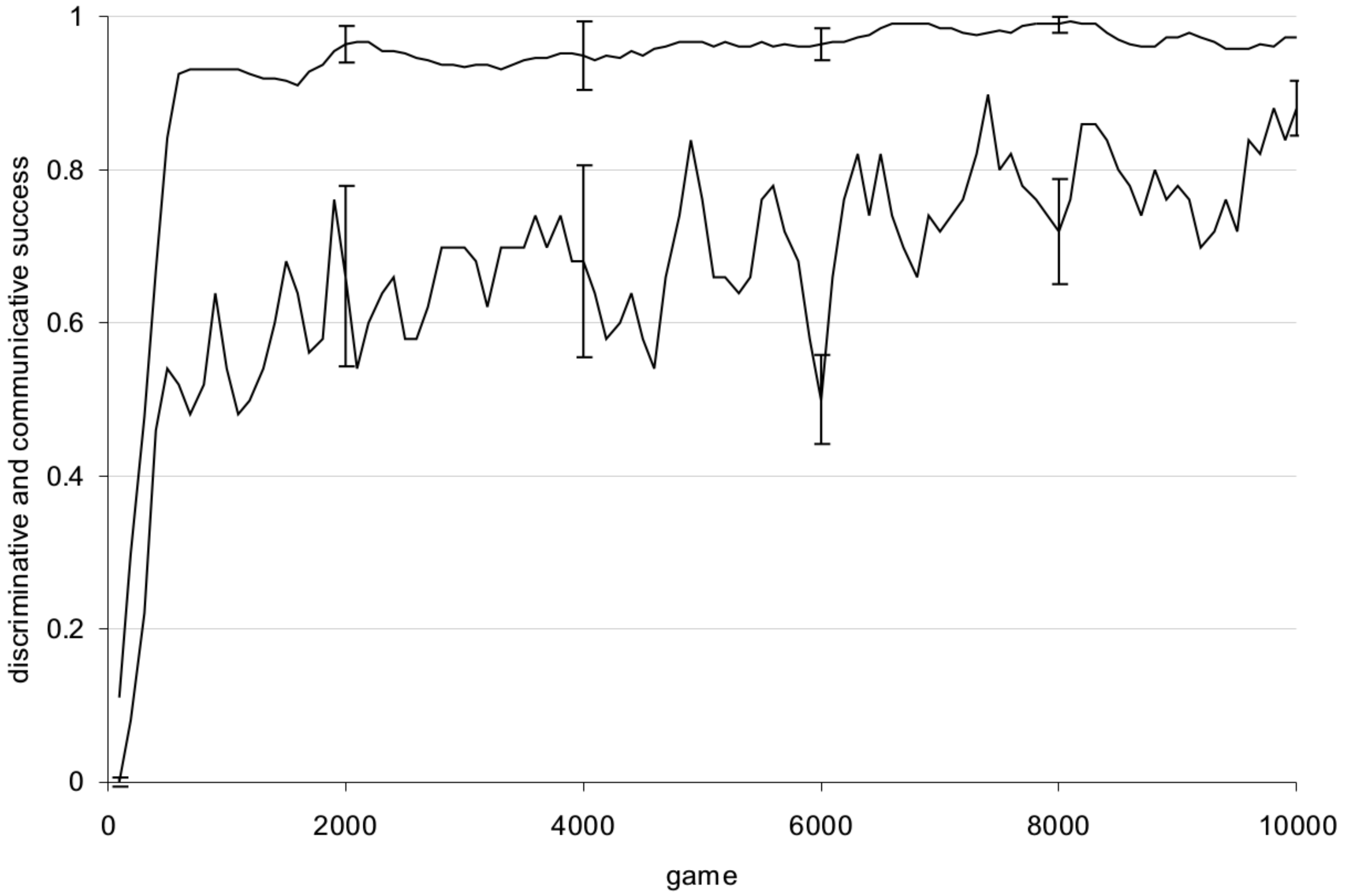
# Effectiveness of learning

Discriminative success: empiricism



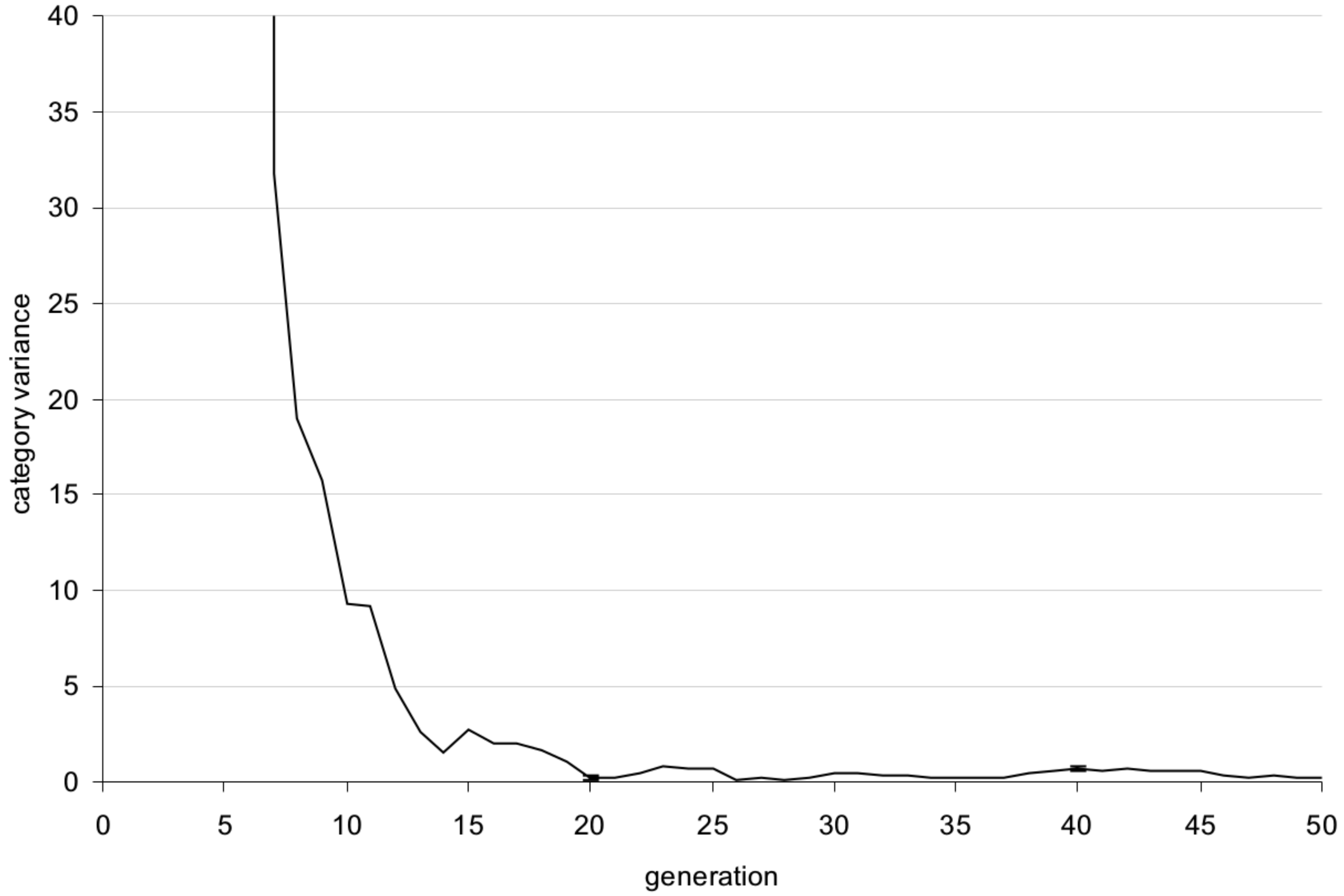
# Effectiveness of learning

Discriminative and communicative success: culturalism



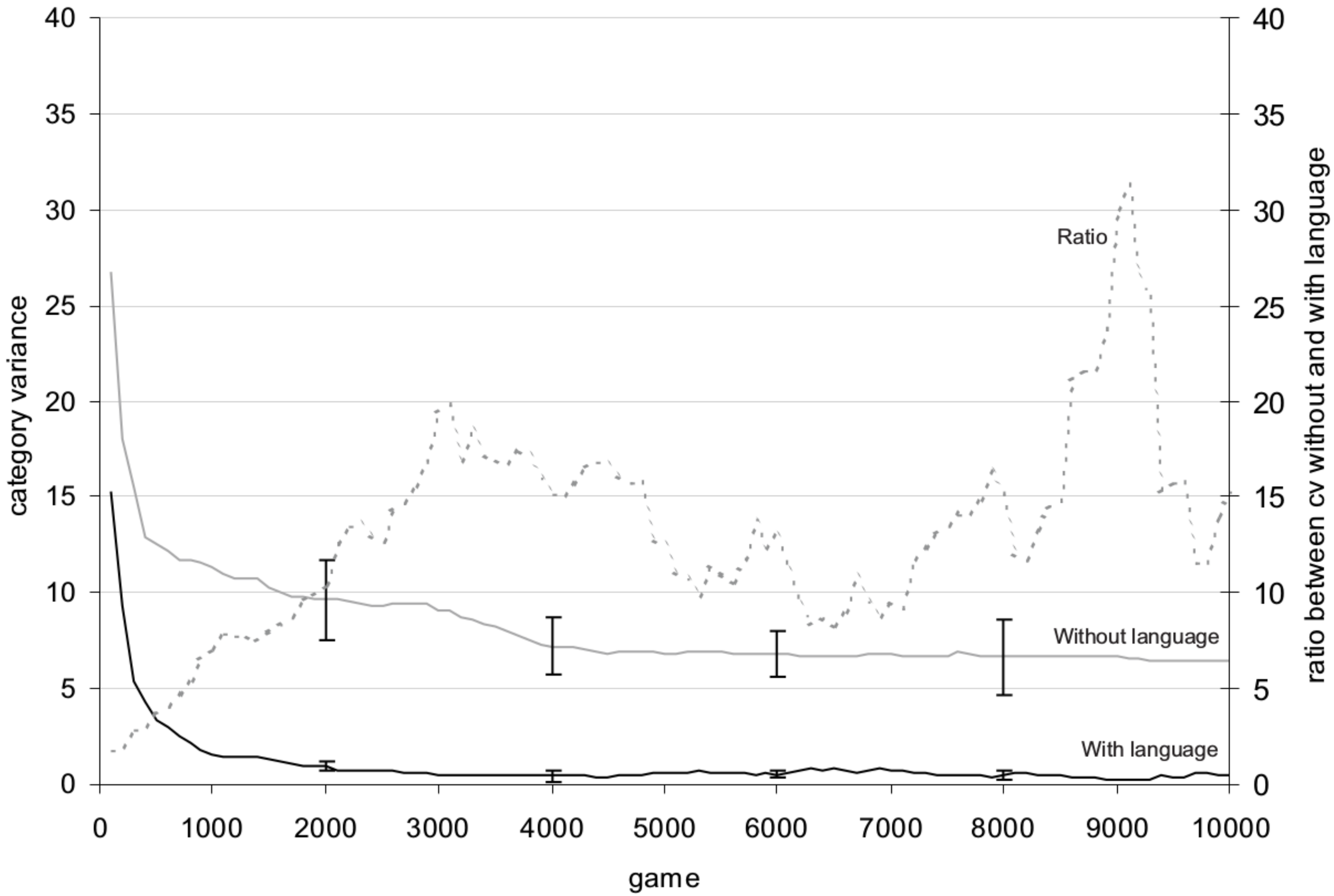
# Effectiveness of learning

## Category variance: nativism



# Effectiveness of learning

Category variance: empiricism vs culturalism



# Cognitive systems simulations: extending the model

# Limitations of the learning model

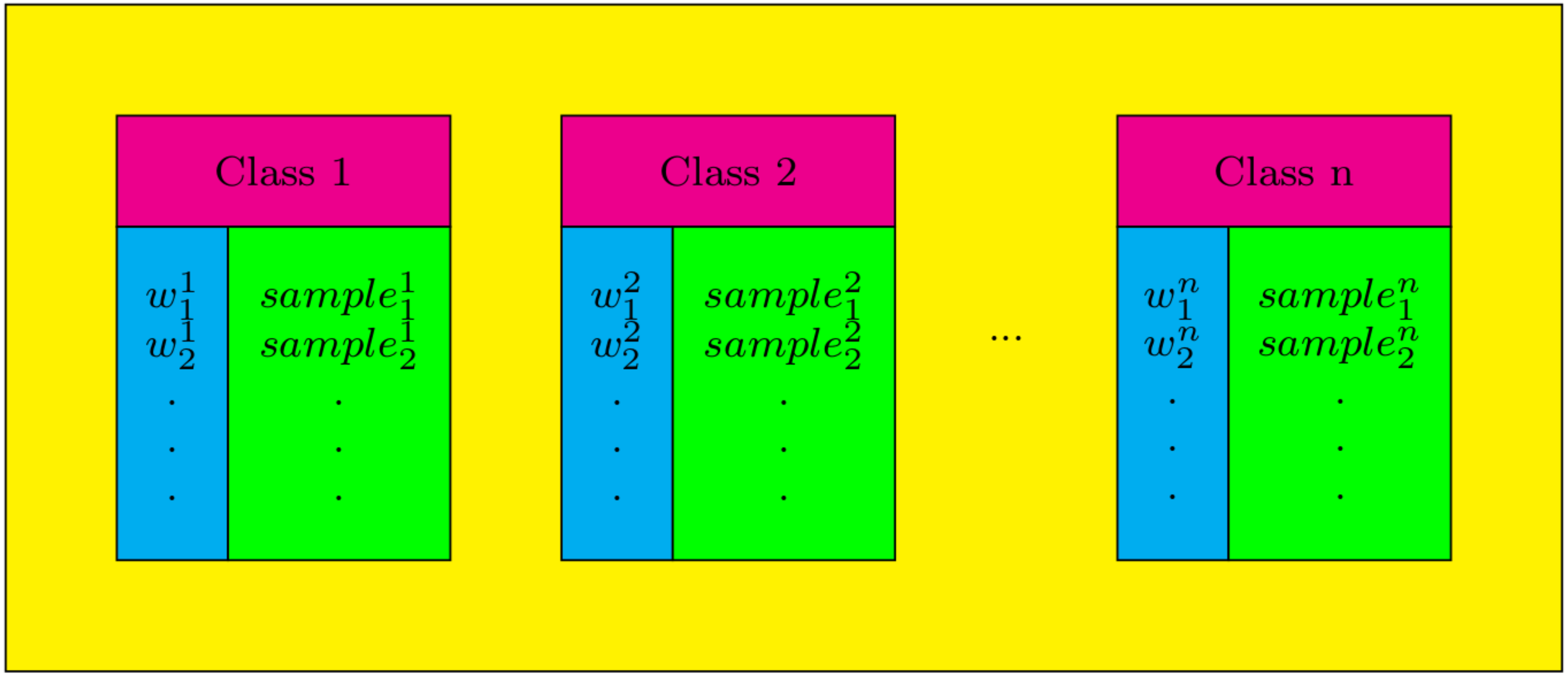
The original learning model was based on radial basis function networks. It was:

- conceptual simple,
- easily adaptive,

but

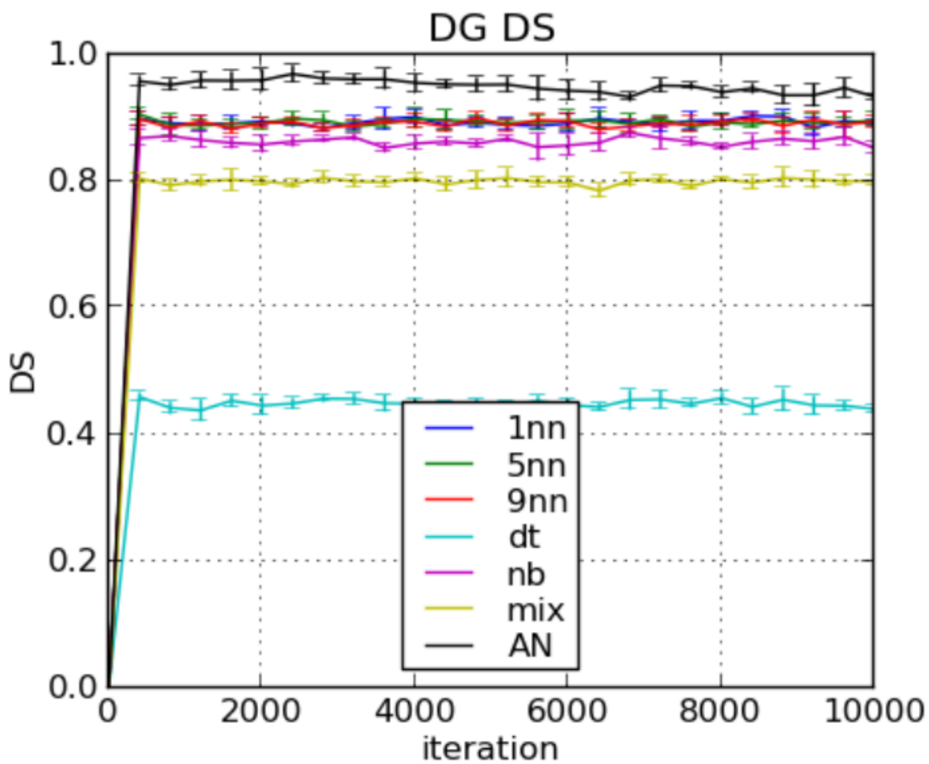
- sensitive to distance function,
- not suitable for more complex stimuli.

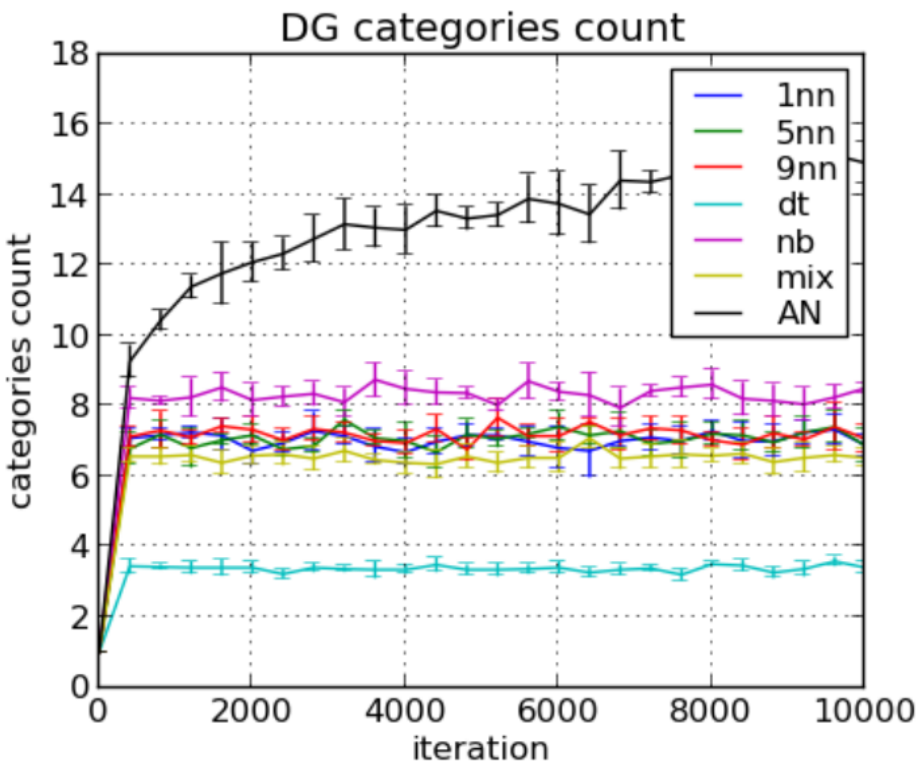
# Reduction to classification problem




Weights of samples are modified after each interaction. Standard machine learning algorithms such as decision trees, k-nearest neighbors or SVMs can be used.

# Performance of machine learning algorithms

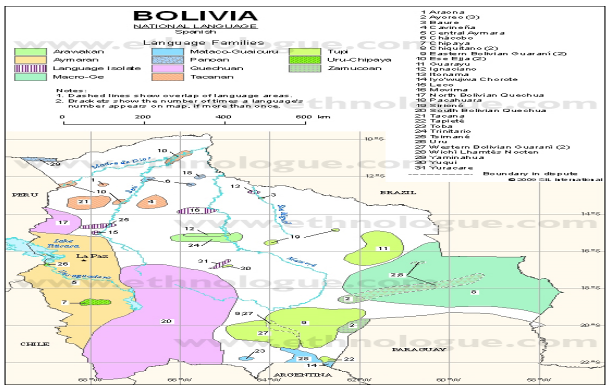


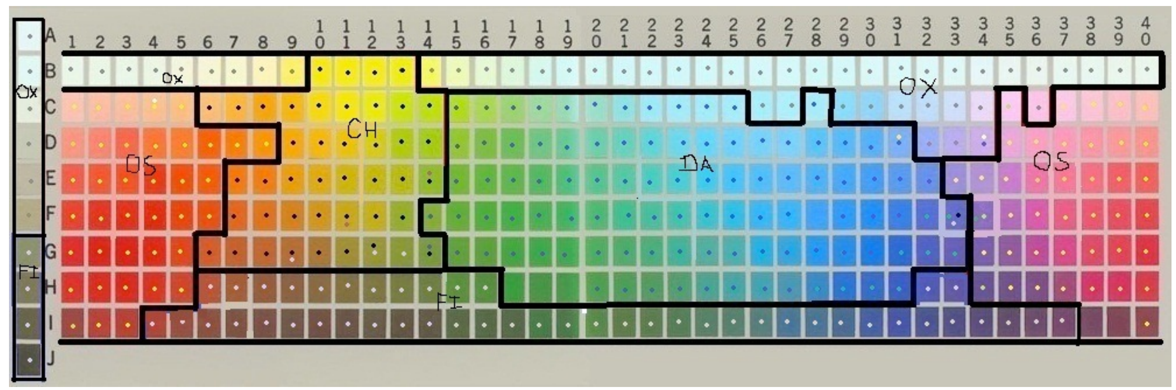



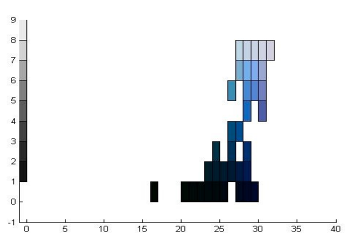
# Cognitive systems simulations: a case study of color

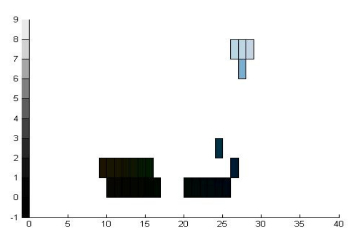
# World color survey

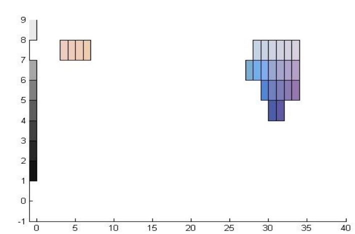
Yaminahua population living in Tropical Forest biome.

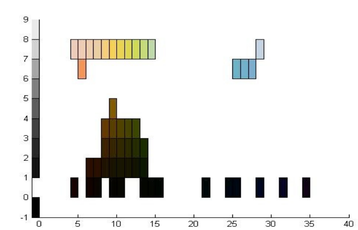








# Does the language describe categories equally?

Each agent describes a category with one word. The most frequent word among the population is the **mode**.

We measure how frequent is the mode value. (*)

* - This corresponds to variance for 0-1 loss.

We play with the distribution of stimuli and check whether it affects frequency of mode value for differnt categories.

# Syntetic colors

**Table 1** Results obtained for simulations on cubic synthetic data. In each cell, number of simulations where average mode was larger on region A and number of simulations where average mode was larger on region B have been shown. Simulation type where region A (B) is 10 times more frequent has been denoted by type A (B).

| Simulation | 1k | 2k | 3k | 4k | 5k | 6k | 7k | 8k | 9k | 10k |
|---|---|---|---|---|---|---|---|---|---|---|
| uniform | 11, 9 | 12, 8 | 13, 7 | 8, 12 | 11, 9 | 11, 9 | 11, 9 | 10, 10 | 12, 8 | 13, 7 |
| type A | 10, 10 | 10, 10 | 14, 6 | 14, 6 | 8, 12 | 12, 8 | 12, 8 | 12, 8 | 10, 10 | 12, 8 |
| type B | 7, 13 | 13, 7 | 6, 14 | 6, 14 | 9, 11 | 11, 9 | 12, 8 | 6, 14 | 9, 11 | 6, 14 |

uniform p-val: 0.09

A p-val: 0.02

B p-val: 0.02

# WCS colors

**Table 2** Results obtained for simulations over 1268 munsell chips data. In each cell, number of simulations where average mode was larger on region C and number of simulations where average mode was larger on region D have been shown. Simulation type where region C (D) is 10 times more frequent has been denoted by type C (D).

| Simulation | 1k | 2k | 3k | 4k | 5k | 6k | 7k | 8k | 9k | 10k |
|---|---|---|---|---|---|---|---|---|---|---|
| uniform | 10, 10 | 9, 11 | 10, 10 | 10, 10 | 5, 15 | 12, 8 | 12, 8 | 10, 10 | 8, 12 | 12, 8 |
| type C | 14, 6 | 15, 5 | 16, 4 | 16, 4 | 17, 3 | 18, 2 | 18, 2 | 18, 2 | 18, 2 | 18, 2 |
| type D | 12, 8 | 14, 6 | 8, 12 | 7, 13 | 9, 11 | 9, 11 | 5, 15 | 5, 15 | 5, 15 | 6, 14 |

uniform p-val: 0.09
C p-val: 2.2e-16
D p-val: 0.002

# Thanks!